ECO 2014/12
Department of Economics

CHINESE IMPORTS COMPETITION'S IMPACT ON EMPLOYMENT AND THE WAGE DISTRIBUTION: EVIDENCE FROM FRENCH LOCAL LABOR MARKETS

Clément Malgouyres

European University Institute
Department of Economics

Chinese Imports Competition's Impact on Employment and the Wage Distribution: Evidence from French Local Labor Markets

Clément Malgouyres

EUI Working Paper **ECO** 2014/12

ISSN 1725-6704

Printed in Italy
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy
www.eui.eu
cadmus.eui.eu

Chinese Imports Competition's Impact on Employment and the Wage Distribution: Evidence from French Local Labor Markets

Clément Malgouyres*
European University Institute

October 2014

Abstract

The rapid rise of Chinese exports over the past two decades has raised concerns for manufacturing employment in high-income countries. Spill-overs beyond manufacturing are an important issue given the large size of the non-traded sector in modern economies and household imperfect spatial mobility. In this paper, I follow the methodology developed by Autor *et al.* (2013a) to estimate the impact of Chinese imports competition onto French local labor markets, with an emphasis on the spill-overs effects beyond manufacturing. I consider a wide array of labor market outcomes, notably the distribution of wages, thus shedding light on the impact of low wage country imports competition on the local degree of wage inequality.

I find that local employment and total labor income in both manufacturing and non-manufacturing are negatively affected by rising exposure to imports. Overall the number of jobs displaced by Chinese imports competition is larger outside than within the manufacturing sector. Jobs destructions are concentrated among low and medium-skill occupations in both traded and non-traded sectors. Hourly wages are negatively affected in both sectors in the middle part of the distribution. Local labor markets strongly exposed to Chinese competition did not experience a rise in the dispersion of hourly wages, with even a reduction of lower-tail inequality in the non-tradable sector. I find evidence suggesting that a high-minimum wage explains this reduction in lower-tail inequality, thus providing a striking illustration of how labor market institutions mediate the effect of globalization-induced shocks to labor demand.

JEL-Classification: F16, J23, J31, R11, R23

*email address: clement.malgouyres@eui.eu. Mail address: Via della Piazzuola 43, 50133 Firenze, Italy. The access to the data was carried through the CASD (Centre d'accès sécurisé à distance) dedicated to researchers authorized by the French "Comité du secret statistique". I thank Jérôme Adda and Andrea Ichino for their guidance and advice. I also thank Wolfgang Dauth, Vincent Maurin, Mark Partridge, Damiaan Persyn and Joao Pessoa for useful comments as well as other participants at EUI Applied Econ WG, ERSA 2013, and IAB SDLM 2014.

1 Introduction

Rising imports competition from low-wage countries and its impact on employment in the manufacturing sector has been a very widely debated issue across the industrialized world. Among low-wage countries, China stands out as the key player. In one decade (1998 to 2008), China's share of world exports went from 3.3 to 9.5 percent, growing at 15 percent annually in value.[1] Figure 1 displays imports and trade balance of France with respect to China and another set of low-wage countries (LWC). China trade's specificity with respect to France, and many high-income countries, stems from the high growth rate of its exports as well as the strong French trade deficit in comparison with other LWCs. Such a sudden rise in imports competition might shrink the manufacturing sector. In turn, decline in manufacturing activity, whether or not triggered by trade shocks, is likely to be associated with a host of local spill-over effects onto local labor markets. Given the large size of the non-traded sector in high-income economies, the question of the transmission of trade shocks outside of manufacturing is of outmost importance for the study of the labor market, especially in its spatial dimension.

In this paper, I study the adjustment of local labor markets in France to the massive increase in Chinese imports competition. This paper contributes to the literature on the impact of trade shocks on local labor markets in two main ways. First, it applies the methodology developed by Autor *et al.* (2013a) with an emphasis on spill-overs outside of manufacturing caused by Chinese imports competition. The rich administrative dataset used allows to look at a wider array of labor markets outcomes by sector and skill-category – employment but also hours worked, total labor earnings. Second, it provide estimates of the impact of Chinese imports competition along the local hourly wage distribution inside and outside of the manufacturing sector. This sheds light on an important aspect of globalization, the rise in North-South trade (deficit), on inequality and the structure

[1] This figures are based on author's own calculation based on UN Comtrade. Hanson (2012) presents a complete pictures of the role of emerging economies, particularly China, in world trade over the last three decades.

of wages in a high-income country with a highly regulated labor market such as France.[2]

I find substantial effect of direct competition on the manufacturing sector. A $-1000 increase in imports exposure per worker causes the manufacturing employment growth to decrease by 6.5 percentage points. This is equivalent to a normalized coefficient of 0.37. Regarding spill-overs to the non-traded sector, I find strong effects on employment, hours worked and wage bills. A $-1000 increase in the imports exposure index is associated with a decline by 4 percentage points of local employment growth rate.[3] Considering that the estimated coefficients capture *absolute changes* and not simply deviation from the aggregate trend, the estimates suggest that, over the period 2001-2007, Chinese imports have led to the displacement of 70,000 and 160,000 jobs in the manufacturing and non-traded sector respectively.[4] In both sectors, jobs destructions are confined to low and middle skill occupations, with the strongest effect for middle-skill occupations in manufacturing and for low-skilled occupations in the non-traded sector. Impacts on average hourly wages are weak and negative in both sectors. Looking at the impact along the distribution of wages, I find contrasting effects across sectors. Wage are uniformly negatively affected in the manufacturing sector, except for the bottom decile. Accordingly there is no increase in wage inequality within the manufacturing sector neither in the bottom (log ratio of the 50th to 10th percentile) or top of the distribution (log ratio of the 90th to 50th percentile). In contrast, in the non-tradable sector, the hourly wages are affected in the lower middle part of the distribution (deciles 2 to 6). Hence, while the average wage impact is not significantly different from 0, the median wage is negatively impacted. While no overall impact on the log ratio of the 90 to 10 percentile is found, this absence of impact reflect a decrease in lower-tail inequality and a rise in upper-tail inequality. The decrease in lower-tail inequality can be rationalized by the strongly bind-

[2]See e.g. Avouyi-Dovi *et al.* (2013) for more information on French labor market institutions regarding collective bargaining and the minimum wage in particular. Overall, employee protection legislation (EPL) is high in France, particularly for permanent contract. The labor market is characterized by a strong duality following the promotion of temporary working contracts (see e.g.Bentolila *et al.* (2010).). The minimum wage is strongly binding with a ratio of minimum to median wage equal to 56% in 2000 and 61% in 2007, above the OECD median (source: OECD dataset on minimum relative to average wages of full-time workers).

[3]This is equivalent to a normalized coefficient of 0.25.

[4]The assumptions required to formulate aggregate statements are discussed in more details in Section 4.

ing minimum wage legislation. While, in the absence of exogenous source of variation in local minimum wage legislation, it is delicate to explicitly test this hypothesis, I provide further evidence backing it by exploiting variation in the degree to which the minimum wage binds at the local level.

This paper belongs to a recent but growing literature using local labor markets as units of observations in order to analyze the impact of change in exposure to imports competition. Typically, within-country cross-sectional variation in changes to trade exposure is obtained by using the fact that local labor markets within a same country differ in their initial sectoral composition and are thus not equally exposed to nation-wide sectoral changes in trade exposure (more detailed are provided in Section 3). A first strand of this literature investigates the impact of changes in trade policy, mainly tariffs. Given absence of major changes in tariffs among developed countries, this literature is mainly focused on developing countries (Goldberg and Pavcnik, 2007). Topalova (2010) analyses the impact of India's trade liberalization during the 1990s on poverty in Indian regions. Kovak (2013) frames his analysis in a classical Ricardo-Viner model of capital specific sector and estimates the impact of trade liberalization in the early 1990s on regional (residual) wages in Brazil. My paper shares a similar empirical approach in that it uses local sectoral specialization interacted with nation-wide sectoral shocks. However I study the impact of Chinese imports competition rather than changes in trade policy and allow the wage effects to vary across sectors (traded versus non-traded sector) and along the distribution. Moreover I investigate non-wage outcomes, such as employment and employment-earnings.

Starting with Autor *et al.* (2013a), a second strand, to which this paper is the most closely related, estimates the impact of Chinese competition onto local labor markets. Working with US commuting-zone data, Autor *et al.* (2013a) interact initial local industrial composition with contemporaneous changes nation-wide sectoral imports to compute an index of exposure to imports competition that captures the value of imports-per-worker faced by each local labor markets. In order to isolate the variation in Chinese exports to the US that is driven by supply factors in China, as opposed to US domestic supply

or demand shocks, they use Chinese exports to other high-income countries as an instrument for actual Chinese exports to the USA. Here, I follow the same empirical strategy and carry out a more detailed analysis in terms of the local transmission of trade shocks outside of manufacturing in terms of sector and prevailing wages. Moreover, given the richness of the administrative dataset used, I can look at effects on hourly rather than weekly wages, thus canceling out variation in labor earnings related to working time and focusing on unit factor price. I am also able to see how such effects vary along the distribution, for each sector, rather than looking at average wages. Dauth *et al.* (2014) look at the impact of Eastern Europe and China trade on German labor markets. They do not find evidence of strong employment effect of Chinese imports competition either inside or outside manufacturing. These findings must interpreted with the specific context of German-China trade which tends to be much more balanced than the US-China trade. France falls closer to the American case in that it has run a large overall trade deficit and in particular with respect to China ($-billion 26 in 2007, i.e. 4.5 percent of France's overall trade, see Figure 1). Lasting trade deficits are likely to be associated with stronger labor market effects as workers and resources, in the absence of a binding balanced-trade condition, need not flow from a subset of the traded sector to another to compensate rising imports.

There has been vibrant debate, both within and outside of academic economics, regarding the impact of globalization on the structure of wages and inequality, however the difficulty to obtain local measure of wage inequality has impeded the application of "local labor market approach" to this issue.[5] Instead most papers on the topic focus on the impact of globalization on job-polarization, that is the disproportional growth of employment in occupations traditionally located at the bottom and top of the wage distribution (see e.g. Autor and Dorn (2013) and Autor *et al.* (2013b)). Alternatively, they examine variation in the college wage premium (e.g. Lindley and Machin (2014)). The exhaustive nature of the data as well as information on hours worked is key here in order

[5]For instance Harrison *et al.* (2011), in their review of recent theoretical and empirical works on trade and within-country inequality, do not cite any papers looking at the impact of globalization on the distribution of wages using the empirical approach used here.

to obtain reliable statistics for different quantiles of the hourly wage distribution for each employment area considered. Moreover, examining outcomes at the local labor market level (rather than industry- or firm-level analysis) offers the crucial advantage of studying the impact of trade-shocks beyond the manufacturing sector, which, in high-income economies, accounts for a limited percentage of overall employment and labor income.

There is a large theoretical literature linking trade and wage inequality. The classic Heckscher-Ohlin framework, considering two factors, high-skill and low-skill, posits that trade should increase the wage gap between skill and non-skill labor in the skill-intensive country.[6] More recent analysis based on less stylized models, featuring for instance labor market frictions (Davidson *et al.*, 1999), firm-heterogeneity and bargaining (Helpman *et al.*, 2010) or fair wage considerations (Egger and Kreickemeier, 2009) lead as well to the conclusion that opening to trade increases wage inequality. It must be noted that a mechanism through which trade increases income inequality in models of international trade with labor market frictions is through an increase in unemployment (e.g. Egger and Kreickemeier (2009); Helpman *et al.* (2010)). However given the nature of the data available, I focus on the price of employed factors, defined here as hourly wage, and do not consider how unemployment risk or difficultly in working full-time is affected by trade in computing the wage distribution. While this can be an important caveat when evaluating the impact on workers welfare,[7] it remains important to see to which extent the structure of wages is affected by imports competition and how this spill-overs onto the service sector. A motivation to resort to analysis along the wage distribution is based on recent models of international trade which suggests that trade increases inequality in ways that is not captured by the observable skill-premium. For instance, Amiti and Davis (2012) develop a model in which an increase in foreign imports competition drives wages up in input-importing and output-exporting firms and reduce wages in firms serving only

[6]The empirical predictions of the basic HOS model has however been largely discredited by the simultaneous rises in wage inequality in both low-skill and high-skill intensive countries Harrison *et al.* (2011).

[7]For instance, the model featuring costly labor mobility between sectors by Artuc *et al.* (2010), trade liberalization can trigger a decline in the wages of import competing industries and nevertheless lead to a rise in lifetime income due to the possible reallocation of the workforce towards exports-oriented industries.

the domestic market. In case the correlation between firms' share of high-skill employees and importer or exporter-status is not perfect, such an increase in inequality would not be captured by using a measure of skill-premium as dependent variable. Looking at the whole distribution of wages allows to capture such an effect while remaining agnostic about the specific mechanism driving the change in the wage distribution.

The rest of paper is structured as follow. In Section 2, I briefly present the data used in this study. Section 3 presents the empirical strategy adopted to identify and estimate the impact of rising Chinese imports competition on a wide array of labor market outcomes. In Section 4, I present and discuss the results regarding employment inside and beyond manufacturing (subsection 4.1), present some extensions and robustness checks (subsection 4.1.3) and display results regarding the wage distribution (subsection 4.2). The conclusion follows.

2 Data

Data for this analysis originates from several sources. Data on employment and wage distribution are drawn from an employer-employee administrative dataset. This database called DADS postes (Déclaration annuelle des données sociales) contains exhaustive data on non-agricultural salaried job-spells in France. I focus mostly on the competitive sector and do not include workers employed by fully public institutions. Statistics are computed at the "employment zone" level.[8] Like the US "commuting area" used in Autor *et al.* (2013a), employment zones' definition is based on a criterion of self-contained commuting which limits the acuity of issues usually associated with spatial contagion across administratively defined units. There are 348 such units according to their 1990 definition.

I document the sector to which a job is associated by using a 4-digit NACE (rev.1) code reported by the plant (establishment) where the job is located. This NACE code is itself determined based on what the main activity of the plant is (not that of the firm). Based on this information, I can distinguish between employment in manufacturing and in the non-traded sector. More importantly I can construct a very accurate index of exposure to

[8] "Zone d'emploi" in French.

Chine products competition (see next section). Regarding French and China's trade, I use UN Comtrade data on from 1995 to 2007. The Harmonized System (HS) nomenclature of year 1992 is mapped into 4-digit NACE sector codes using conversion tables available on Eurostat's website RAMON. More details are provided in Appendix A. I restrict the sample to jobs occupied by workers aged between 16 and 64, with strictly positive earnings and hours worked. I aggregate data at the non-traded versus traded level for each area-year (1995, 2001 and 2007) and take the first difference of the data and obtain a final dataset of 348 areas observed over two 6-year periods.

Some data regarding private employment during the 1980s (1982 to 1990) and as well as the share of college graduates are taken from public available census data, for the waves 1982, 1990 and 1999. The two latter are respectively associated with year 1995 and 2001.

Summary statistics are presented in Table 1. The average size (measured by non-auxiliary jobs) of an employment zone was 180,000 in 1995, with a median about half the mean, suggesting some skewness. With almost 2 millions worker, the Paris employment area is a clear outlier in terms of size. All results presented below are robust to the exclusion of this area. Employment in manufacturing declined during both periods, although much more markedly between 2001 and 2007 than between 1995 and 2001. Hours worked per job are on average much higher in the manufacturing sector than in the non-traded sector (1600 versus 1290 in 1995). Hours worked might thus provide a more comparable and relevant measure than job count when comparing impact of Chinese competition across sectors. High and medium skill occupations account roughly for 30 % of employment.[9] The variables ΔIPW and ΔDPW stand for changes in, respectively, imports per worker (IPW) and trade deficit per worker (DPW). The precise definition of these variables is given in section 3. For now, it is sufficient to see that the two variables are very close, owing to the fact that the rise in French-Chinese trade is mainly driven by France's rising purchases of Chinese products. Moreover, it appears that there has been an acceleration in the pace of imports/trade deficit growth between the two periods.

[9]The exact definition of low, medium and high skill workers will is given in Section 4.1.3.

3 Empirical Strategy: Measurement and identification

In this section I describe the empirical strategy adopted to estimate the direct impact of Chinese imports competition. To measure the local exposure to Chinese imports, I build on Autor *et al.* (2013a) and compute a index of imports exposure, called "Imports-per-Worker". This index interacts initial local industrial composition of the manufacturing sector with contemporaneous nation-wide Chinese imports by sector.

Formally, the index ΔIPW is defined according to the following formula:

$$\Delta IPW_{it} = \sum_{s=1}^{N_S} \frac{L_{ist}}{L_{st}} \Delta M_{st} \tag{1}$$

where ΔM_{st} stands for the changes in Chinese exports to France between periods t and $t+1$ for sector s, L_{st} is equal sector s employment in France for at time t. L_{it} is total employment in area/period i, t while L_{ist} is employment in area i in sector s at time t.[10]

To estimate the impact of Chinese imports penetration on some local labor market outcomes Y (e.g. employment in manufacturing etc.), I use the following baseline specification:

$$\Delta \log Y_{it} = \Delta IPW_{it}\beta + X'_{it}\delta + \eta_t + \varepsilon_{it} \tag{2}$$

To fix ideas, consider the case where $\Delta \log Y_{it}$ is the growth rate of employment in the manufacturing sector. There are many plausible reasons why in specification (2), ΔIPW might be correlated with the error term ε even after controlling for an extensive set of covariates (discussed more in depth in the next section). Nation-wide sector specific shocks (supply or demand) are partly driving the amount of goods imported in France from abroad. If these shocks affect simultaneously sectoral imports and labor demand,

[10]This variable is thus closely related to the widely used Bartik-instrument Bartik (1991) in that it interacts initial sectoral composition and contemporaneous sector-wide trends. Note however, that I use ΔIPW_{it} as a *causal* variable and not as an instrument. In fact, the breadth of the outcomes affected by ΔIPW_{it} could raise concerns about the plausibility of the exclusion-restriction when using the Bartik-instrument to instrument for changes in local employment or unemployment.

OLS estimates will be biased. To formalize this idea, let us consider the case where the error term ε_{it} can be decomposed between **(i)** a weighted sum of nation-wide sectoral supply and demand shocks (which we denote w_s and x_s respectively) and **(ii)** an error term uncorrelated with any other terms included in the regression. For simplicity we omit the time subscript:

$$\varepsilon_i = a_S \sum_s \lambda_{is} w_s + a_D \sum_s \lambda_{is} x_s + \epsilon_i$$

where the parameter a_S and a_D determines the sign and magnitude of the impact of supply and demand shocks, respectively, on manufacturing employment growth and λ_{is} is an unobserved term representing the "importance" of sector s in location i (a simplification could be to set it equal to $\frac{L_{ist}}{L_{it}}$, i.e. the initial employment share of sector s in location i). Collecting sectoral shocks w_s and x_s respectively in vectors $\mathbf{w}$ and $\mathbf{x}$, noting $\mathbf{m}$ the vector containing the changes in imports to initial employment ratios (with typical element $m_s = \frac{\Delta M_s}{L_s}$) and $\theta_{is} = \frac{L_{ist}}{L_{it}}$ the share of sector s in total employment in location i, and omitting exogenous regressors for simplicity, we can rewrite equation (2) as:

$$\Delta \log Y_i = \beta \theta_i' \mathbf{m} + \lambda_i'(a_S \mathbf{w} + a_D \mathbf{x}) + \varepsilon_i \tag{3}$$

This specification is reminiscent of panel model with interactive fixed-effect (Bai, 2009) in the sense that the unobserved heterogeneity term λ_i is multidimensional (the length of vector λ_i is here equal to the number of sectors in the economy) and is allowed to interact with shocks that are common through the rest of the cross-sectional units.

Hence OLS estimation of the main specification will be biased due the covariance between ΔIPW_i and $\lambda_i'(a_S\gamma + a_D\psi)$ which we can write as:[11]

$$\text{cov}(\theta_i'\mathbf{m}, \lambda_i'(a_S\mathbf{w} + a_D\mathbf{x})) = a_S\theta_i'\text{cov}(\mathbf{m}, \mathbf{w})\lambda_i + a_D\theta_i'\text{cov}(\mathbf{m}, \mathbf{x})\lambda_i$$

[11] In the derivation of this expression I consider θ_i and λ_i as fixed parameter vectors and $\mathbf{m}$ and $\mathbf{w}$ as random vectors.

If we assume that $s \neq s' \Rightarrow \text{cov}(m_s, w_{s'}) = \text{cov}(x_s, w_{s'}) = 0$ which amounts to ignoring cross-sectors relationships (driven for instance by input-output linkages or substitution in consumption between goods), we get the following expression:

$$\text{cov}(\theta_i'\mathbf{m}, \lambda_i'(a_S\mathbf{w} + a_D\mathbf{x})) = a_S \sum_s \theta_{is}\lambda_{is}\text{cov}(m_s, w_s) + a_D \sum_s \theta_{is}\lambda_{is}\text{cov}(m_s, x_s) \quad (4)$$

We expect the covariance between nationwide unobserved sectoral supply shocks and imports-per-worker ($\text{cov}(m_s, w_s)$) to be negative. When French producers in sector s are subject to a negative supply shock ($w_s < 0$ e.g. mandatory nation-wide reduction in weekly working-time with no reduction in monthly wages), one would expect an increase in purchase in goods s from foreign suppliers, including China and other low-wage countries. That suggests $\text{cov}(m_s, w_s) < 0$. On the other hand, as x_s represents demand shocks, one would expect that $\text{cov}(m_s, x_s) > 0$.

Positive supply and demand shocks are expected under general conditions to increase employment, hence we can assume $a_S > 0$ and $a_D > 0$. According to this framework, the bias introduced by unobserved sectoral shocks could either be positive or negative depending on the relative magnitude of supply and demand shocks and how they affect imports from low-wage country. Because these nation-wide shocks affect each community differently, through to the vector λ_i, including periods fixed-effects does not solve the issue.

We resort to an instrumental variable strategy whereby we instrument actual exports from low-wage countries to France by Chinese exports to a set of high-income countries whose economic cycle is weakly related to that France.[12] The formula for the instrument is the following:

$$\Delta IPW_{it}^o = \frac{1}{L_{it}} \sum_s \frac{L_{ist}}{L_{st}} \Delta M_{st}^o \quad (5)$$

where ΔM_{st}^o is Chinese exports to the set of selected other high-income countries.

[12]The list of countries is almost the same as in Dauth *et al.* (2014), except that it excludes the United Kingdom and includes Denmark, South-Korea, Argentina and Chile. The list includes the following countries: Australia, Canada, Japan, New Zealand, Norway, Singapore, Sweden, and South Korea. Note tat we excluded all countries from continental Europe which are part of the euro zone.

The identifying assumption underpinning the validity of this instrument is that Chinese exports to these countries, i.e. the vector ΔM^o, are independent from domestic shocks in France (contained in vectors $\mathbf{w}$ and $\mathbf{x}$ in our example) so that the statistical association between French imports from China and Chinese exports to these high-income countries is only driven by supply-side improvements in China. This assumption seems credible given that China underwent major economic reforms since the 1980s which accelerated over the 1990s, culminating with China's accession to the World Trade Organization in 2001. These reforms were deeply influenced by China's own domestic politics and decided independently from development pertaining specifically to France.[13] The choice of other high-income countries is such that they represent a small percentage of French exports so that the exclusion restriction appears credible.

Figure 2 contain three maps of France regarding IPW and employment growth over the 2001-2007 period. Table 1 shows that decline in manufacturing has taken place over the 2 periods but was much stronger over the second one. Imports and Trade deficit per worker grew faster over the second period as well. Figure 3 displays the first-stage, plotting observations from both periods (after taking out period fixed-effect) as well as best linear fit and a 95 % confidence interval. Figure 4 display the first stage for the long-differences. In both cases, the instrument is a strong predictor of the endogenous regressor ΔIPW_{it}. The first-stage Kleibergen-Paap F-statistic for the stack specification with no-covariate is 41 way above the critical value of 16 suggested by Stock and Yogo (2005) for 2SLS estimates. The corresponding reduced-forms with respect to manufacturing and non-traded employment are plotted in the Figures 5 and 6.

The period we cover stretches from 1995 to 2007. The choice of the beginning date is driven by data availability regarding local sectoral composition, wages and hours worked. The end of the period is marked by the onset of the Great Recession which deeply affected trade flows as well as GDP in ways that is very likely to be correlated across high-income countries, thus making the identifying assumption less credible over the

[13]For an extensive account of Chinese reforms, subsequent growth and increasing economic openness see Brandt and Rawski (2008).

post-2007 period.[14]

4 Results

4.1 Employment and Total Earnings

4.1.1 Manufacturing sector

The first specification measures the impact of IPW on employment and total hours worked in the manufacturing sector. Results are displayed in Table 2. All specifications include the initial value of overall employment in the employment area.[15] Column (1) implies that a $ 1000 increase in ΔIPW is associated with a 6.4 percentage point decrease in manufacturing employment growth rate. We see in Column (2) that instrumenting ΔIPW by ΔIPW^o yields a higher (in absolute value) coefficient of -10. Considering the formula for OLS bias in Equation (4), it suggests that, under the maintained hypothesis that the instrument is exogenous, France's increasing imports of Chinese products are for a substantial part explained by French idiosyncratic demand shocks that boost both employment and imports thus causing an upward bias in OLS estimates. This result is similar to what is found for the US case for by Autor *et al.* (2013a). In Column (3), we control for the initial share of employment in the manufacturing sector. Under this specification, variation across employment areas comes only from differences in the local specialization within the manufacturing sector and not from differences in terms of share of the manufacturing sector as a wole. It uses the fact that Chinese imports growth has been very uneven across subsets of the manufacturing sector. The inclusion of that term does not affect substantially the estimate, which is equal to -8.[16]

[14]Figure 1 shows the decline in imports from China occurring in 2008/2009.

[15]This control accounts for the fact there tends to be a negative relationship between city population and its growth rate, as pointed in Card (2007) and Faggio and Overman (2014).

[16]Unlike Autor *et al.* (2013a), I do not consider employment over population but growth rate in employment (and other outcomes). This choice is mainly dictated by the data. The years considered (1995,2001,2007) do not correspond to a census year. Hence there is no data on overall working age population. Overall adult (above 18) population, as opposed to working age population (which would typically include the 16 to 65 year olds) can be approximated by the number of registered voters for the presidential elections of 1995, 2001 and 2007. In a set of unreported regression, I show that adult population proxied by registered voters do not respond to China-induced trade shocks. Results are available upon request. In the absence of reaction of population adjustment, trade shocks' impact on the

Column (4) and Column (5) test the robustness of the results, relaxing further the identifying assumptions required to interpret the coefficient causally. Column (4) adds a series of additional controls that discards some potential confounding factors. It controls for the initial share of college-educated residents, of women, foreigners, and production workers in the workforce. Including these controls allows each employment area to have a specific trend proportional to each of these initial shares. The rational to include production workers is to account for the potential exposure of employment areas to technical change and automatization that could possibly lead to a decline in labor demand by the manufacturing sector independently from globalization (Autor and Dorn, 2013). Women's labor supply is often found to be considerably more elastic than that of men.[17] Hence, a shock of a given size to local labor demand might carry more or less impact on overall employment depending on the local share of women in the workforce. Finally, the share of college graduates accounts for the fact that there has been an increasing gap in employment and unemployment rates between college and non-college educated individuals. The estimate decrease marginally in magnitude from Column (3) to Column (4) with an absolute value of 7.1. In Column (5) includes "region"-fixed effects[18], thus allowing each region to have a specific trend. Again, we do not see a large decline in the estimate which, at a value of 6.4, remains significant at the 1 percent level.

I now put these results into perspective and gauge their economic significance. It is important to note that the first-difference approach adopted in this paper identifies the *relative impact* of *changes* in trade exposure. In that sense it identifies how local labor markets exposed to Chinese competition deviate from the aggregate trend. In our setting, making aggregate predictions necessitates additional assumptions such that the coefficient associated with ΔIPW reflect *absolute* changes in outcomes and not simply changes *relative* to the aggregate trend. In fact, aggregate prediction requires period fixed-effects not to be a function of the regressor aggregated across employment zones.[19] This as-

change of log employment translates roughly one-to-one to the change in the log ratio of employment to adult population.

[17]See Bargain *et al.* (2014) for recent internationally comparable results on the topic.

[18]There are 22 so called "Regions" in metropolitan France.

[19]See Appendix B for a more formal argument.

sumption is not necessary in order to obtain consistent estimates of imports competition impact on local labor markets but I adopt it in this paragraph in order to, somewhat heuristically, get an order of magnitude of the estimated effect if it was to reflect absolute changes.[20] Between 1995 and 2007, employment in the manufacturing sector declined by 14.4 percent. It declined by 1.7 percent over the last period (1995-2001) and declined by 13.3 percent over the second period (2001-2007).[21] I predict import-driven changes in growth rate in manufacturing by using our 2SLS estimates times the observed change in import-per-worker at the local level times the share of variation in imports explained by Chinese supply-side factors. I deduce this share from the R-square of a simple bivariate regression of ΔIPW_{it} on ΔIPW^o_{it} (after partialling out all covariates included in Column (5)).[22] This simple computation allows to retrieve the nation-wide effect of Chinese imports penetration on manufacturing employment. I find a nation-wide effect of -0.27 and -1.44 percentage-points for the first and second periods respectively. Hence, under the stated assumptions, we find that Chinese imports are responsible for about 11 percent of the decline in the French manufacturing sector employment over the period 2001-2007. In terms of jobs, that implies that imports Chinese competition destroyed 14,000 jobs over the first period and 73,000 jobs over the second. This exercise is therefore consistent with the notions that (i) trade with China have become increasingly relevant for industrial employment in developed economies, (ii) other factors, such as technological change, lie behind the rapid decline of industrial employment in France.

Columns (6) and (7) apply the same specification as in Column (5) changing only the dependent variable. Columns (6) shows the impact on total hours worked. The estimate is very close to that in Column (5) suggesting no change in average hours worked per job. This is interesting in the light of the widespread notion that imports competition has promoted part-time and unconventional forms of employment (source). Column (7)

[20]This point is also discussed in Topalova (2010).

[21]These figures are based on the exhaustive job-level dataset "DADS postes" when aggregated at the sector/year level for all of France.

[22]The predicted change for employment zone i at time t is thus equal to: $g_{it} = R^2 \times \beta \times \Delta IPW_{it}$ where R^2 refers to the partial first-stage R-square. The aggregate predicted change is then simply: $\overline{g}_t = R^2 \times \beta \times \overline{\Delta IPW}_t$, where $\overline{x}_t$ means the average of variable x across the cross-section at time t.

looks at overall employment earnings (hours worked times hourly wage). The impact is sensibly larger than that on hours worked suggesting a mild decline in the average hourly wage. This is confirmed in Column (8) which finds a statistically significant (at the 5 % confidence level) impact of imports competition on average wage. This result contrasts with those of Autor *et al.* (2013a) who find no effect on average weekly wage within manufacturing. Although downward wage rigidity (nominal or real) is a salient feature of the manufacturing sector, it is not incompatible with this finding. Indeed the present results reflect the effect on wage growth in deviation from aggregate trends and could be explained by low wage for the new hires or simply a lower albeit positive wage growth rate.

4.1.2 Outside of manufacturing

Main impact on the non-traded sector

I now turn to the effect of Chinese imports penetration employment and hours worked in the non-traded sector as a dependant variable. The results are displayed in Table 3. The effect is weaker and less precisely estimated. The weaker effect found on the non-traded sector can be explained by the fact that there is a decline in demand for non-traded output, employers in this sector benefit from a positive local labor supply shocks as a share of workers displaced from the manufacturing sector are likely to be looking for jobs locally. Normalizing variables, estimate from Column (5) suggests that a one standard deviation increase in ΔIPW cause a decline in non-traded employment of 0.23 standard deviation. We notice that estimates in Column (6) and (7) are very similar and that unlike in the manufacturing sector in that average hourly wage is not significantly affected.

Under the same assumptions as in the previous paragraph, I can get an order of magnitude regarding the aggregate impact of Chinese imports competition on job displacement in the non-traded sector.[23] Using the formula explained in footnote 4.1.1 leads to the

[23]The use of the word displacement rather than destruction is warranted by the fact jobs in the non-traded sector, following a local trade shock, are very likely to be moved to a new location and not purely destroyed. In fact, there has been positive growth in non-traded sector employment over the period considered suggesting that the estimated impact are local in nature. This contrast with the generalized

conclusion that local growth in non-traded employment was reduced by 0.20 over the first period and 1.42 over the second. This suggests that 270,000 jobs in the non-traded sector were displaced due to spill-overs associated with China-induced trade shocks between 2001 and 2007, a much larger number than what is found for the manufacturing sector.

The impact of Chinese imports competition onto the non-tradable sector is indirect in that it operates through its impact on the manufacturing sector. The ratio of the estimates from tables 3 and 2 are similar to a "local multiplier effect" (Moretti, 2010) in the sense that it defines the elasticity of non-tradable employment to employment in the manufacturing sector.[24] Taking estimates of Column 3 from both tables leads to a ratio of 0.66, which given an average ratio of non-traded to manufacturing employment of 2.5 suggest a job-to-job effect of 1.65. Moretti (2010) resorts to the Bartik-instrument to estimate directly the impact of growth in tradable employment on the growth of the non-tradable sector. He finds an impact of about 1.6, a figure very close to the present findings, especially considering that he does not use imports competition as a source of variation in local manufacturing employment. This suggests that shocks to local labor demand induced by trade-shocks trigger spill-overs of the same magnitude as those captured by the Bartik-instrument, which encapsulates sectoral shocks of all sources (e.g. domestic demand shock, technological shocks etc.) by using directly nation-wide changes in sectoral employment (Partridge *et al.*, 2013).

Decomposing the impact on the non-traded sector

I look into a finer decomposition of the impact of the non-traded sector. Table 4 shows how the spill-overs associated with rising Chinese imports competition on the local manufacturing sector vary across different subsets of the non-traded sector. The table

decline in manufacturing employment.

[24] To see this, recall that the coefficients on ΔIPW of Table 3 and 2 are semi-elasticities of, respectively, non-traded and traded employment with respect to ΔIPW: $\beta_{Non-Traded} = \frac{\partial \Delta \ln(L_{Non-Traded})}{\partial \Delta IPW}$ and $\beta_{Traded} = \frac{\partial \Delta \ln(L_{Traded})}{\partial \Delta IPW}$ where L_s refers to employment in sector s. Therefore the ratio yields an elasticity $\frac{\beta_{Non-Traded}}{\beta_{Traded}} = \frac{\partial \Delta \ln(L_{Non-Traded})}{\partial \Delta \ln(L_{Traded})}$.

contains two panels, the upper panel displays results for the specification without region-fixed effects and the lower one with region fixed-effects.

Focusing first on the upper panel, the most strongly affected industries are construction (Column 1) and hiring services (Column 2). Hiring services includes temporary workers. Hence the large effect on that sector can be rationalized by the fact (i) these workers are typically the adjustment buffer firms resort to first when adjusting the size of their labor force, (ii) a large share of such workers are "lent" to the manufacturing and construction sector. Clearly, a share of the decline in employment in temporary work comes the direct effect of trade shocks on manufacturing. It is not possible from currently available data to know in which types of firms temporary workers are actually employed. Therefore I cannot precisely decompose the trade-induced decline in temporary work in its direct and indirect components. Construction is a sector that by definition is very non-tradable. It is also very intensive in temporary work (DARES, 2009), therefore part of the jobs shredded by construction firms are counted in Column (2) in the "hiring services". Yet, despite this underestimation, the impact on the construction sector are large which confirms the intuition that the producers of hardly tradable output are heavily impacted by decline in local demand. The rest of the traded sector is also affected, although to a much lower extent. The estimate for business services, except hiring services, is strongly negative but imprecisely estimated (p-value = 12.7%). These results contrast with Dauth *et al.* (2014) who find virtually no effect of trade shocks on the non-traded sector besides the business service sector that is very intensive in temporary workers lent to the manufacturing sector. In the lower panel we can see that the inclusion of region-fixed effects reduces most point-estimates and mostly alters their precision. Only the impact of construction remains significant, although the coefficient for hiring services is almost significant at the 10 % level (p-value of 10.5 %).

4.1.3 Robustness Checks and extensions

Placebo regressions

In spite of the extensive set of controls, as well as the instrumentation of ΔIPW, there remains the suspicion that results displayed so far could be picking up a secular decline of employment in some local labor markets. I test this possibility by regressing employment growth on lead values of ΔIPW. If future values of ΔIPW predicts current low job growth, it could could imply that estimates presented until now are picking up the impact of an omitted factor correlated with rising imports competition (for instance labor-saving technological change). I use data from the French Census for periods 1982-1990 and 1990-1999 an compute overall private employment growth and resort to the administrative data, used in the rest of the analysis, for the 2001-2007. Table 5 displays the results. In columns (1) and (2), employment growth in the private sector (reexpressed in 6 year period equivalent growth rate) for periods 1990-1999 and 2001-2007 is regressed on ΔIPW for periods 1995-2001 and 2001-2007. In columns (3) and (4), employment growth in the private sector (reexpressed in 5 year period equivalent) for periods 1982-1990 and 1990-1999 is regressed on ΔIPW for periods 1995-2001 and 2001-2007. Focusing on the IV regression results, we can see that while ΔIPW is associated with a decline in contemporaneous employment growth (Column 2), it is associated with higher growth rate in lagged employment, suggesting that the negative coefficients estimated above reflects a causal impact of Chinese imports competition on job growth rather than a secular decline. On the contrary, employment areas with high lead values of ΔIPW were experiencing above average growth in employment during the 1980s and 1990s.

Impact by skill-category

Retaining the specification of Column (6) from Table 2 and 3, I now estimate skill-specific impact of imports competition sector-by-sector. As is usual with administrative data, there is no information on workers' educational achievements, therefore I use a definition of skill based on occupations. I break down employment into three broad categories (low, medium and high skill) based on so-called "social and professional cat-

egories". Employees and production workers are associated with low-skill, medium-skill contains "intermediary professions" and high-skill includes "managers and intellectual professions".[25] The upper panel of Table 7 display results for the manufacturing sector. It shows that negative effect of imports competition are concentrated in low-skilled and medium-skilled occupations in manufacturing sector. These findings are consistent with a polarizing effect of imports competition on the job composition, as intermediary jobs are markedly more affected than low-skill occupations and high-skill jobs are not significantly impacted. This is also consistent with the process of skill-upgrading caused by Chinese imports competition at the firm-level detected by Mion and Zhu (2013). The previous result on average wage growth should be interpreted in light of this compositional effect: despite considerable skill-upgrading (as measured by shift in the occupational structure of the manufacturing sector), the Chinese imports competition had an overall negative effect on average hourly wages.

The lower panel shows estimates for the non-tradable sector, depicting broadly similar patterns. However, job losses are more concentrated in the low-skill occupations and magnitude are on average lower. We also notice a significantly positive effect on the growth rate of high-skill occupations. Measuring the share of non-traded sector jobs that are taken up by individuals previously employed in the manufacturing sector would shed light on the reallocation process triggered by imports competition and how people initially employed in the non-traded sector are affected.

Net imports

Dauth *et al.* (2014) emphasizes that local labor markets can be positively affected by trade. Chinese economic growth is associated with a surge in imports. If some local labor markets are specialized in sectors for which Chinese demand grows particularly fast, Chinese growth could stimulate local labor demand. As shown in the introduction and in Figure 1, French-Chinese trade is particularly unbalanced. In 2007 for instance, French

[25]This codification follows Caliendo *et al.* (2012) who use the same database (DADS) to analyze the hierarchical organization of French firms.

exports to China amounted $-bn 14 while its imports amounted to $-bn 40, thus leaving a deficit of $-bn 26 equivalent to 4.5 % of French total trade (exports plus imports). In this section, I check whether considering net imports (or trade deficit) as opposed to overall imports lead to substantially different estimates. I do not test exports and imports separately mainly because I do not dispose of a relevant and valid instrument for French exports to China.[26] Table 6 based on the same specifications as in Table 2 with the only exception that the variable imports per workers has been replaced by a "deficit-per-worker" variable. Coefficients are very close to those in Table 2, although of a somewhat larger magnitude. It is logical as the deficit-per-worker nets out any positive effect associated with rise in exports that would not be captured by the gross imports measure.

These estimates provide some information regarding what would have been the impact in terms of manufacturing employment of balancing trade with respect to China. [27] Given that the average increase in ΔDPW has been 690 over last period 2001-2007, given a partial R-square of ΔDPW on ΔIPW^o equal to 0.13, in the absence of increase in trade deficit , manufacturing employment would have grown by 0.80 percentage point more, representing about 40,000 jobs (based on coefficient displayed in Column 5).

4.2 Effect on the Distribution of Wages

There is by now a large body empirical work showing that changes in imports exposure has a very heterogenous impact across firms. For instance, Bloom *et al.* (2011) find that surge in Chinese imports competition has a negative employment effect that is considerably smaller for innovative firms. Amiti and Davis (2012) shows that, following a trade liberalization episode in Indonesia, large exporters or importers increased their wages relative to firms serving the domestic market only. As explained in the introduction, such heterogeneous effects along firm-level characteristics will be associated with increase in

[26]Imports by China of products made in other high income countries could be a possible instrument. The strength of such instrument is however very low, owing to the fact that Chinese product basket of imported goods vary a lot across provenance-countries, much more so than its export basket (which is quite uniform as attested by the strength of the first-stage).

[27]Balancing trade is equivalent to setting the average deficit per worker (ΔDPW) from its average value to 0

wage dispersion in ways that are unlikely to be fully captured by a variable pertaining to individual-level skill, such as college education or type of education. On the other hand such impact will be reflected in the overall distribution of wages. In this section, I estimate the impact of Chinese imports competition on each decile of the wage distribution, thus capturing overall changes in wage dispersion while remaining agnostic about which the particular mechanism through which Chinese imports competition is affecting inequality.

The upper panel of Table 8 displays the results regarding the manufacturing sector. All deciles but the bottom one are significantly negatively affected by imports competition. The estimate is very imprecisely estimated for the 1st decile, resulting in an insignificant coefficient in spite of a very large point estimate. The impact for the median is somewhat lower than the effect on the average wage. More over the highest estimates are those for the 8th and 9th deciles. Hence, the distribution of hourly wage in manufacturing is not made less egalitarian by exposure to imports competition, instead it's been uniformly decreased except for the bottom decile. Most estimates are barely significant, note however that only results based on the most stringent specification are displayed. Unreported coefficients based on the same specification without region-fixed yield very similar point estimates with more precision.[28]

The lower panel of Table 8 displays results for the non-traded sector. We see that the non-significant effect on average wage hides considerable heterogeneity across deciles. There are strong effects in the middle-part of the distribution, between the 2nd and 7th deciles included. The impact on the median wage is much stronger than that on the average wage. The median wage effect is of the same magnitude as in the manufacturing sector and is more precisely estimated. This shows that trade shocks are diffused to the local non-tradable sector. Here again the bottom decile is not significantly affected, with a point estimated very close to zero. A binding minimum wage could be a reason behind this absence of effect (more on this below). There is also no significant impact on the

[28]The results are available upon request.

two top deciles.

In Table 9, we report how different measures of wage dispersion/inequality have been affected by China-induced trade shocks. Column (1) displays the estimated effect on changes in the log of 90th to 10th percentile ratio of the local wage distribution. While the coefficient is positive for manufacturing, it is very imprecisely estimated. It is very close to 0 and insignificant in the non-tradable sector as well. Hence it appears, based on that measure of inequality, that that Chinese imports competition, while it had some notable impact on wage and on employment did not move affected local labor markets away from the general trend towards compression of the French wage distribution over the period considered (Verdugo, 2014). We decompose the change of the log ratio of the 90th to 10th percentile into the sum of the change of the log ratio of the 50th to 10th percentile (lower-tail inequality) plus the change of the log ratio of the 90th to 50th percentile ratio (upper tail inequality). In the case of manufacturing, although point estimates suggest a rise in lower-tail dispersion, none is significantly different from zero. In the non-traded sector however, it appears that null effect of imports competition on the 90t to 10t percentile ratio results from a combination of increase in upper-tail dispersion (Column 2) and compression in the lower-tail of the distribution (Column 3). Here again, the binding role of the minimum wage provides a plausible explanation to these findings.

The minimum wage is nationally set in France and there is no variation in the legal definition of the minimum wage across employment areas or sectors of employment.[29] It is however more or less binding, meaning that there is variation in the share of workers working at the minimum wage across locations and sectors. We use this variation to test the hypothesis whether a binding minimum wage explains the absence of impact of trade shocks on the lower decile of the wage distribution. If in a given employment area and sector, more than 10 % of jobs are paid are the minimum wage, then, one would not expect any impact of trade-induced demand shocks on the bottom decile of the wage distribution. Inversely, employment areas where less than 10 % of jobs are paid at the minimum wage, the bottom decile of the distribution is exposed to the downward pressure

[29]While there are some legal exemptions to the minimum wage, they account for a small share of the population, see Kramarz and Philippon (2001).

associated with negative labor demand shocks. I introduce an interaction term between ΔIPW and a binary variable equal to 1 if less than 10 % of employees (in manufacturing or the non-tradable sector depending on which sector the dependent variable pertains) in the initial year of the period are paid at the minimum wage. This interaction term is then instrumented by the product of ΔIPW^o and the binary variable. Noting S_{10} the binary variable, the specification we estimate is the following:

$$\Delta \log q_{10,it} = \Delta IPW_{it} \cdot \beta_1 + \Delta IPW_{it} \times S_{10,it} \cdot \beta_2 + X'_{it}\delta + \eta_t + \varepsilon_{it} \tag{6}$$

Following the line of reasoning exposed above, one would expect β_1 to be close to zero, and β_2 to be negative, meaning that wage losses are concentrated in areas/sector where the minimum wage is not binding for the first decile. There are obvious limitations to this exercise, as the initial share of minimum wage employees could be considered endogenous to posterior growth in the 1st decile of the wage distribution. There could be for instance some unobservable characteristics affecting both minimum wage ratios and subsequent wage growth rate. Note however that intuitively, one would expect such unobservables to cause high minimum wage ratio and lower wage growth. On the contrary, our hypothesis states low minimum wage ratios should be associated with lower wage growth when associated with strong exposure rise in Chinese imports competition. Consequently, endogeneity of low minimum wage local ratio seems likely to introduce an upward bias in estimates that we expect to be negative.

Table 10 presents the results separately for the manufacturing and non-manufacturing sector. Column (1) displays results for the manufacturing sector. Results are as expected: the estimate associated with the interaction term is significantly negative while that on ΔIPW is not significantly different from 0. Results from Column (2) are based on a specification where S_{10} is directly introduced, thus allowing each employment area to follow a different trend depending on wether its initial share of minimum wage workers exceeds 10 %. Point estimates remain remarkably stable but are less precisely estimated and not significantly different from 0 at the 10 % level. Regarding the non-traded sector, results show more clearly that areas where the first decile was not covered by the

minimum wage experienced a negative impact of imports competition, while the others were (unsurprisingly) protected. Column (4) shows that low minimum wage ratio areas have a higher unconditional trend in terms of the growth rate of their bottom decile (2 % higher), but also that Chinese competition induced strong negative impact on the bottom decile in these areas (-4.4%).

5 Conclusion

Local employment and total labor income in the manufacturing sector are reduced in employment areas more exposed to Chinese imports. The effect goes beyond manufacturing sector as non-traded employment is also significantly affected. The estimates suggest that the number of jobs displaced is higher in the non-traded than in the traded sector. The strongest employment impact is concentrated on medium and low skill occupations in the the traded and non-traded sector respectively. Contrary to previous works in trade and local labor market literature (Autor *et al.*, 2013a; Dauth *et al.*, 2014), wage rates are found to be negatively affected by Chinese imports competition but there is no increase in overall wage rate inequality. Notably, in none of the sector is the bottom decile affected, and the non-traded sector's lower tail inequality is even reduced. This is true only in areas where the minimum wage is covering more than 10% workers (implying that the lower decile is in fact equal to the minimum wage). This result provides a striking example of how labor market institutions mediate the effect of globalization-driven shocks on wage dispersion.

The present study highlights the rising impact of low-wage competition on local labor markets. The presence of large local multiplier effects associated with large trade-induced displacements combined with evidence that there is little labor mobility in response to shocks in local demand suggest that trade shocks have locally concentrated effects that are likely to be long-lasting. These trends contribute to explain the popularity of place-based policies that generally aim at tempering the local consequences of labor demand

shocks. The design and implementation of optimal place-based policies in the presence of strong local labor demand shocks and workers low spatial mobility seem therefore an important area for further research.

References

Amiti, M. and Davis, D. R. (2012). Trade, Firms, and Wages: Theory and Evidence. *Review of Economic Studies*, **79** (1), 1–36.

Artuc, E., Chaudhuri, S. and McLaren, J. (2010). Trade Shocks and Labor Adjustment: A Structural Empirical Approach. *American Economic Review*, **100** (3), 1008–45.

Auer, R. A., Degen, K. and Fischer, A. M. (2013). Low-wage import competition, inflationary pressure, and industry dynamics in Europe. *European Economic Review*, **59** (C), 141–166.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, **103** (5), 1553–97.

—, — and Hanson, G. H. (2013a). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, **103** (6), 2121–68.

—, — and — (2013b). *Untangling Trade and Technology: Evidence from Local Labor Markets*. NBER Working Papers 18938, National Bureau of Economic Research, Inc.

Avouyi-Dovi, S., Fougere, D. and Gautier, E. (2013). Wage Rigidity, Collective Bargaining, and the Minimum Wage: Evidence from French Agreement Data. *The Review of Economics and Statistics*, **95** (4), 1337–1351.

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, **77** (4), 1229–1279.

Bargain, O., Orsini, K. and Peichl, A. (2014). Comparing labor supply elasticities in europe and the united states: New results. *Journal of Human Resources*, **49** (3).

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* No. wbsle in Books from Upjohn Press, W.E. Upjohn Institute for Employment Research.

Bentolila, S., Cahuc, P., Dolado, J. J. and Le Barbanchon, T. (2010). *Two-Tier Labor Markets in the Great Recession: France vs. Spain*. IZA Discussion Papers 5340, Institute for the Study of Labor (IZA).

Bloom, N., Draca, M. and Reenen, J. V. (2011). *Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity*. NBER Working Papers 16717, National Bureau of Economic Research, Inc.

Brandt, L. and Rawski, T. G. (eds.) (2008). *China's Great Economic Transformation*. Cambridge University Press, cambridge Books Online.

Caliendo, L., Monte, F. and Rossi-Hansberg, E. (2012). *The Anatomy of French Production Hierarchies*. Working Paper 18259, National Bureau of Economic Research.

Card, D. (2007). *How Immigration Affects U.S. Cities*. CReAM Discussion Paper Series 0711, Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London.

DARES (2009). L'interim en 2008. *Premieres syntheses*, (27).

Dauth, W., Findeisen, S. and Suedekum, J. (2014). The rise of the east and the far east: German labor markets and trade integration. *Journal of the European Economic Association*, pp. n/a–n/a.

Davidson, C., Martin, L. and Matusz, S. (1999). Trade and search generated unemployment. *Journal of International Economics*, **48** (2), 271–299.

Egger, H. and Kreickemeier, U. (2009). Firm Heterogeneity And The Labor Market Effects Of Trade Liberalization. *International Economic Review*, **50** (1), 187–216.

Faggio, G. and Overman, H. (2014). The effect of public sector employment on local labour markets. *Journal of Urban Economics*, **79** (C), 91–107.

Goldberg, P. K. and Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, **45** (1), 39–82.

Hanson, G. H. (2012). The Rise of Middle Kingdoms: Emerging Economies in Global Trade. *Journal of Economic Perspectives*, **26** (2), 41–64.

Harrison, A., McLaren, J. and McMillan, M. (2011). Recent Perspectives on Trade and Inequality. *Annual Review of Economics*, **3** (1), 261–289.

Helpman, E., Itskhoki, O. and Redding, S. (2010). Inequality and Unemployment in a Global Economy. *Econometrica*, **78** (4), 1239–1283.

Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review*, **103** (5), 1960–76.

Kramarz, F. and Philippon, T. (2001). The impact of differential payroll tax subsidies on minimum wage employment. *Journal of Public Economics*, **82** (1), 115–146.

Lindley, J. and Machin, S. (2014). Spatial changes in labour market inequality. *Journal of Urban Economics*, **79** (C), 121–138.

Mion, G. and Zhu, L. (2013). Import competition from and offshoring to China: A curse or blessing for firms? *Journal of International Economics*, **89** (1), 202–215.

Moretti, E. (2010). Local multipliers. *American Economic Review*, **100** (2), 373–77.

Partridge, M. D., Rickman, D., Olfert, M. R. and Tan, Y. (2013). *International Trade and Local Labor Markets: Are Foreign and Domestic Shocks Created Differently?* MPRA Paper 53407, University Library of Munich, Germany.

Stock, J. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, New York: Cambridge University Press, pp. 80–108.

Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics*, **2** (4), 1–41.

Verdugo, G. (2014). The great compression of the French wage structure, 1969–2008. *Labour Economics*, **28** (C), 131–144.

Table 1: Descriptive statistics

	Period 1995-2001			Period 2001-2007		
	Mean	Std dev.	Median	Mean	Std dev.	Median
Initial employment in thousands	180.3	220.2	88.2	197.2	241.4	103.3
% employment in mfg (initial)	28.8	9.4	27.6	24.4	8.7	23.5
% chge in manufacturing empl.	-1.7	10.1	-1.0	-13.3	9.1	-13.1
% chge in non-tradable sector empl.	25.4	5.5	25.3	8.0	7.0	8.1
% medium skill jobs (in total emp.)	20.1	3.3	20.1	20.1	3.2	20.1
% high skill workers (in total emp.)	10.5	5.0	9.0	9.9	5.5	7.9
Hours worked per job: manufacturing	1609.7	69.6	1614.1	1491.5	65.2	1492.7
Hours worked per job: non-traded sector	1293.8	42.4	1298.7	1153.6	42.3	1153.7
ΔIPW in \$-thousands (2001)	0.168	0.121	0.134	0.898	0.585	0.718
ΔDPW in \$-thousands (2001)	0.148	0.131	0.117	0.698	0.621	0.0512

Notes: See Equation 1 for definition of ΔIPW and ΔDPW. Except for the first line, all averages are computed using 1995 total employment are weights.

6 Tables

Table 2: Direct impact of Chinese imports competition on manufacturing

	(1) OLS: Jobs b/se	(2) IV b/se	(3) IV b/se	(4) IV b/se	(5) IV b/se	(6) IV: Hrs b/se	(7) IV: Emp. earnings b/se	(8) IV: Hrly wage b/se
ΔIPW	-6.492***	-10.067***	-7.975***	-7.121***	-6.439***	-6.293***	-9.111***	-1.790*
	(1.305)	(1.914)	(2.094)	(2.040)	(1.855)	(1.775)	(2.111)	(0.914)
% employment in mfg (initial)			-0.142**	-0.176***	-0.100	-0.097	0.039	0.093***
			(0.062)	(0.068)	(0.066)	(0.070)	(0.074)	(0.031)
% college				-0.689***	-0.344***	-0.381***	-0.439***	0.174***
				(0.163)	(0.123)	(0.125)	(0.134)	(0.059)
% production workers				-0.454***	-0.204*	-0.221*	-0.252**	0.027
				(0.101)	(0.114)	(0.115)	(0.127)	(0.056)
% women				-1.353**	-1.746***	-1.885***	-2.155***	-0.069
				(0.660)	(0.485)	(0.573)	(0.676)	(0.322)
% foreigners				-0.370*	-0.481**	-0.469**	-0.512**	-0.074
				(0.206)	(0.190)	(0.210)	(0.230)	(0.065)
KP stat		40.52	26.56	26.74	27.84	27.84	27.84	27.84
Region fixed-effect					√	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 3: Impact of Chinese imports competition on the nontradable sector

	(1) OLS: Jobs b/se	(2) IV b/se	(3) IV b/se	(4) IV b/se	(5) IV b/se	(6) IV: Hrs b/se	(7) IV: Emp. earnings b/se	(8) IV: Hrly wage b/se
ΔIPW	-1.832***	-4.479***	-5.328***	-5.015***	-4.055***	-2.210**	-2.903***	-0.508
	(0.599)	(1.160)	(1.363)	(1.329)	(0.991)	(0.877)	(0.972)	(0.348)
% employment in mfg (initial)			0.058	0.037	0.181***	0.165***	0.201***	0.049***
			(0.045)	(0.048)	(0.048)	(0.046)	(0.048)	(0.015)
% college				-0.453***	-0.171	-0.244**	-0.432***	-0.073**
				(0.141)	(0.108)	(0.105)	(0.114)	(0.035)
% production workers				-0.210**	0.122	0.047	0.000	-0.090***
				(0.083)	(0.096)	(0.091)	(0.099)	(0.027)
% women				-0.800*	-1.091**	-1.232***	-1.192**	-0.017
				(0.446)	(0.452)	(0.434)	(0.486)	(0.127)
% foreigners				0.088	-0.147	-0.196	-0.233	-0.013
				(0.151)	(0.157)	(0.155)	(0.173)	(0.044)
KP stat		40.52	26.56	26.74	27.84	27.84	27.84	27.84
Region fixed-effect					√	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 4: Heterogeneity within the non-tradable sector

	(1) Construction b/se	(2) Temp. work b/se	(3) Hotels b/se	(4) Retail b/se	(5) Business b/se	(6) Transport b/se	(7) Rest b/se
Specification with controls and no region-fixed effects							
ΔIPW	-5.024***	-7.525*	1.677	0.352	-4.113	1.273	-2.446*
	(1.924)	(4.049)	(1.770)	(1.680)	(2.693)	(1.803)	(1.474)
KP stat	26.74	26.74	26.74	26.74	26.74	26.74	26.74
Full set of controls (see notes)	√	√	√	√	√	√	√
Specification with controls and region-fixed effects							
ΔIPW	-3.150**	-6.155	2.526	1.237	-1.912	1.078	-1.690
	(1.456)	(3.805)	(1.771)	(1.537)	(2.204)	(1.703)	(1.316)
KP stat	27.71	27.71	27.71	27.71	27.71	27.71	27.71
Full set of controls (see notes)	√	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 5: Placebo regression: private employment growth regressed on lead values of import competition

	(1) OLS: Private b/se	(2) IV: Private b/se	(3) OLS: Lagged b/se	(4) IV: Lagged b/se
ΔIPW	-2.548***	-4.039***	-0.820	2.320***
	(0.421)	(0.902)	(0.691)	(1.042)
KP stat		27.84		27.84
Controls (see notes)	√	√	√	√
Region fixed-effect	√	√	√	√
N	696	696	696	696

Notes: Column 1 and 2 respectively report OLS and IV estimates of specification shown in Equation (2) where the dependent variable is current employment growth rate (in equivalent of 6 years) in the overall private sector. Column 3 and 4 respectively report OLS and IV estimates of the same specification where employment growth in the private sector is lagged (1982-1990 for period 1995-2001, 1995-2002 for period 2001-2007). In case, long run unobserved factor driving down manufacturing employment in local labor markets is correlated with future exposure to Chinese imports competition, one would expect to find negative coefficients in the Column 3 and 4.

Table 6: Trade deficit per worker: impact on manufacturing employment

	(1) OLS: Jobs b/se	(2) IV b/se	(3) IV b/se	(4) IV b/se	(5) IV b/se	(6) IV: Hrs b/se	(7) IV: Hourly Wage b/se
ΔDPW	-5.023***	-12.470***	-10.344***	-9.116***	-8.231***	-8.044***	-2.287*
	(1.237)	(2.999)	(3.374)	(3.144)	(2.760)	(2.563)	(1.228)
% employment in mfg (initial)			-0.117	-0.143*	-0.072	-0.070	0.101***
			(0.072)	(0.078)	(0.075)	(0.078)	(0.034)
% college				-0.690***	-0.312**	-0.350***	0.182***
				(0.164)	(0.127)	(0.128)	(0.061)
% production workers				-0.500***	-0.192	-0.210*	0.030
				(0.104)	(0.117)	(0.119)	(0.057)
% women				-1.489**	-1.866***	-2.002***	-0.102
				(0.696)	(0.505)	(0.592)	(0.325)
% foreigners				-0.354	-0.483**	-0.471**	-0.074
				(0.225)	(0.214)	(0.231)	(0.062)
KP stat		20.42	12.18	12.57	13.61	13.61	13.61
Region fixed-effect					√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01.

Table 7: Impact on employment by skill category: manufacturing and non-traded sector

	(1) Low Skill b/se	(2) Intermediate Skill b/se	(3) High skill b/se	(4) Low Skill b/se	(5) Intermediate Skill b/se	(6) High skill b/se
Manufacturing						
ΔIPW	-4.066**	-15.096***	-1.466	-3.253*	-14.561***	-1.544
	(1.864)	(3.847)	(4.154)	(1.676)	(3.699)	(4.072)
Non-traded sector						
ΔIPW	-5.909***	-2.980*	5.686**	-4.987***	-1.899	4.950**
	(1.420)	(1.662)	(2.513)	(1.099)	(1.386)	(2.400)
KP stat	27.84	27.84	27.84	27.84	27.84	27.84
Full set of controls (see notes)	√	√	√	√	√	√
Region fixed-effect				√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Skill categories are based on occupation. Clerk and unskilled production workers are considered low skill occupations. Intermediate professions and low-rank managers are considered medium skill occupations, while intellectual professions, senior management are considered high-skill occupations.

Table 8: Impact along the wage distribution in manufacturing and the non-traded sector

	(1) Av. wage b/se	(2) 10th pctile b/se	(3) 20th b/se	(4) 30th b/se	(5) 40th b/se	(6) 50th b/se	(7) 60th b/se	(8) 70th b/se	(9) 80th b/se	(10) 90th b/se
Manufacturing										
ΔIPW	-1.790*	-3.377	-1.635*	-1.766*	-1.599*	-1.295	-1.358	-1.685*	-2.562**	-2.163**
	(0.914)	(2.292)	(0.891)	(0.902)	(0.905)	(0.906)	(0.926)	(0.988)	(0.995)	(1.088)
Non-traded sector										
ΔIPW	-0.508	0.053	-0.811***	-1.045***	-1.349***	-1.250***	-1.178***	-1.064***	-0.509	-0.031
	(0.348)	(0.313)	(0.277)	(0.286)	(0.313)	(0.314)	(0.338)	(0.375)	(0.425)	(0.533)
KP stat	27.84	27.84	27.84	27.84	27.84	27.84	27.84	27.84	27.84	27.84
Full set of controls (see notes)	√	√	√	√	√	√	√	√	√	√
Region fixed-effect	√	√	√	√	√	√	√	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Decile are computed based on jobs reporting positive hours worked and wages, weighing by hours worked.

Table 9: Effect of Chinese imports competition on different measures of wage inequality

	(1) $\Delta \log \frac{q_{90}}{q_{10}}$ b/se	(2) $\Delta \log \frac{q_{90}}{q_{50}}$ b/se	(3) $\Delta \log \frac{q_{50}}{q_{10}}$ b/se
Manufacturing			
ΔIPW	1.214	-0.868	2.082
	(2.240)	(1.079)	(1.783)
	(1) b/se	(2) b/se	(3) b/se
Non-traded sector			
ΔIPW	-0.085	1.219**	-1.304***
	(0.593)	(0.514)	(0.383)
KP stat	27.84	27.84	27.84
Full set of controls (see notes)	√	√	√
Region fixed-effect	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. Control variables include: initial share of manufacturing jobs, of female employees, of production employees, of foreign-born employees and of college educated employees. Decile are computed based on jobs reporting positive hours worked and wages, weighing by hours worked.

Table 10: Impact on the first decile depending on the share of workers covered by the minimum wage

	(1)	(2)	(3)	(4)
	Manufacturing		Non-traded sector	
ΔIPW	-0.801	-0.788	0.096	0.051
	(0.832)	(0.565)	(0.314)	(0.311)
$\Delta IPW \times$ Share Min Wage < 10 %	-4.409*	-4.441	-2.554***	-4.407***
	(2.621)	(3.684)	(0.503)	(0.780)
Share Min Wage < 10 %		0.038		1.947***
		(1.303)		(0.356)
KP stat	18.23	19.47	13.80	13.75
Full set of controls (see notes)	√	√	√	√
Region fixed-effect	√	√	√	√

Notes: $N = 696$. Baseline sample is a balanced panel of 348 employment zones. Outcomes variables are expressed in percentage change over six-year period. All specifications include period fixed effect and log of initial total employment. Robust standard errors are clustered at the employment zone level. *p<.10 ** p<.05, *** p<.01. The share of minimum wage workers is computed as the share of workers in a given location and sector who hourly wage (*salaire brut horaire*) is comprised between 85 and 105 % of the legal minimum wage. Observations whose wage is reported below 85 % of the minimum wage are dropped.

7 Figures

Figure 1: Imports and trade balance of France with respect to China and other low-wage countries (list based on Auer *et al.* (2013))

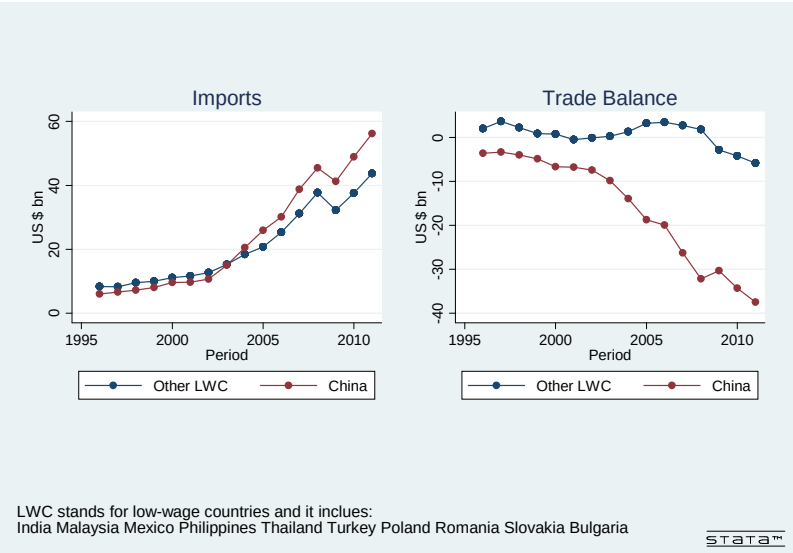
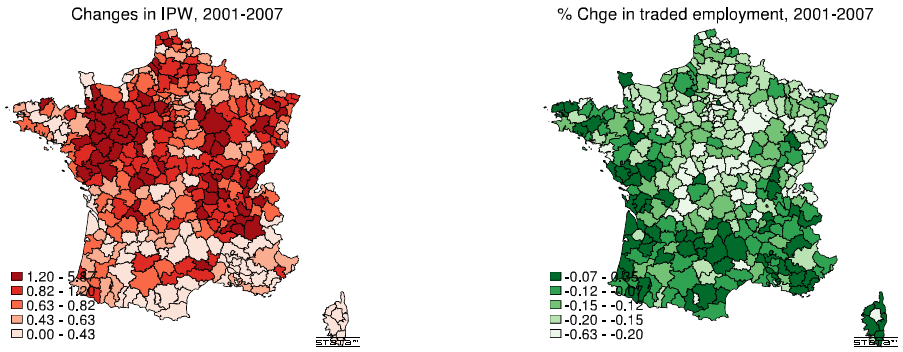
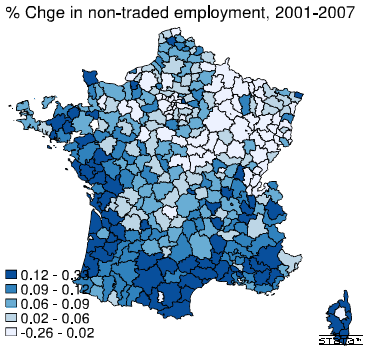


Figure 2: The geography of trade exposure and employment growth, 2001-2007

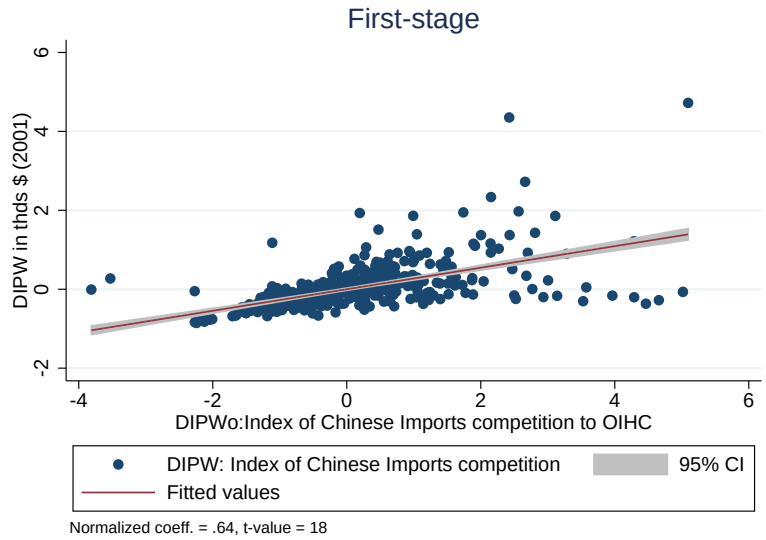


(c) The Geography of Non-Tradable Employment



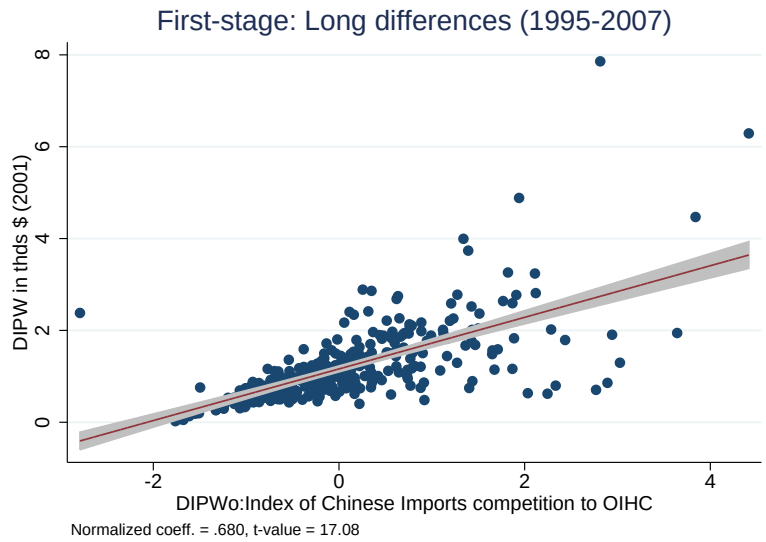
Notes: Black boundaries delimitates employment zones. Each shade corresponds to a quintile of the distribution of the relevant variables.

Figure 3: First stage: Stacked periods



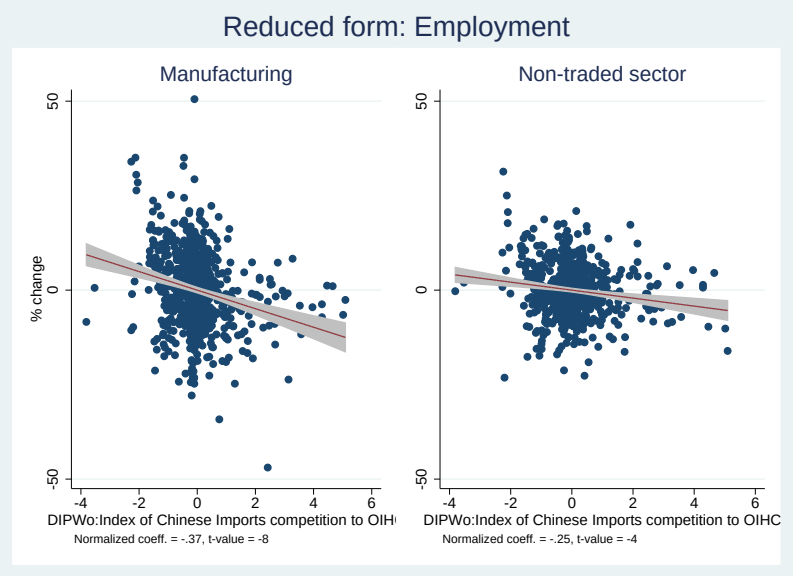
Notes: Each dot represents an employment zone for a given period (1995 to 2001, 2001 to 2007). Variables are expressed in deviation from period average.

Figure 4: First stage: Long-differences



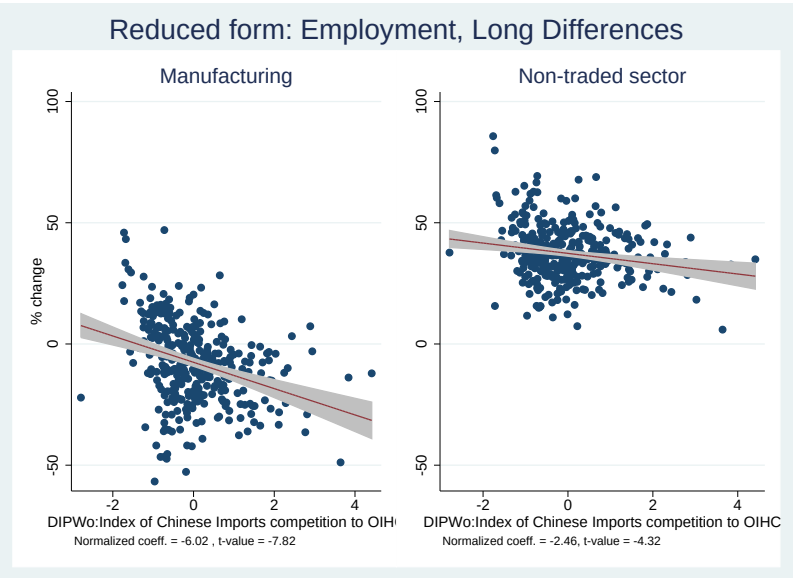
Notes: Each dot represents a employment zone over the 12 year period 1995-2007.

Figure 5: Reduced form: Stacked periods



Notes: Each dot represents an employment zone for a given period (1995 to 2001, 2001 to 2007). Variables are expressed in deviation from period average.

Figure 6: Reduced form: Long-differences



Notes: Each dot represents a employment zone over the 12 year period 1995-2007.

A Linking trade and employment data

We use data on trade from the website `un.comtrade.org`. The trade data follow the product classification HS 1992 with 6 digit. The data on employment follows the NACE rev 1.1. classification which is equivalent to the 4-digit CPA 2002 classification. To convert HS-1992 6-digit codes into NACE 4-digit codes, we do the following:

1. We use a file available on `un.comtrade.org` to map HS-1992 into HS-2007.

2. We use one file available on `http://ec.europa.eu/eurostat/ramon` to map HS-2007 into CPA 2002. The latter maps n-to-one to the NACE rev 1.1.

3. We obtain a correspondence mapping from HS-1992 into NACE rev. 1.1 and drop all HS-1992 6-digit goods that are not uniquely mapped with a NACE 4-digit sector. Dropped observations account for about 9 %, 8 % and 6% of French imports from China for years 1995,2001 and 2007 respectively.

Alternatively, trade flows for not-uniquely mapped HS-1992 products could divided across sectors using weights reflecting each sectors initial "importance" in the economy (employment for instance). Applying this method using employment in 1995 as weights do not modify the present results.

Table 11: Total French Imports: Uniquely and Non-Uniquely Mapped ($ millions)

	Total	Uniquely	Non-uniquely	Ratio
1995	5,950	5,385	565	.095
1996	6,833	6,236	597	.0873
1997	7,495	6,874	621	.0828
1998	8,178	7,505	673	.0823
1999	8,943	8,237	706	.079
2000	10,515	9,670	845	.0803
2001	10,450	9,635	815	.078
2002	11,380	10,506	874	.0768
2003	15,850	14,660	1,190	.0751
2004	21,398	19,871	1,527	.0714
2005	26,748	24,737	2,011	.0752
2006	30,968	28,652	2,316	.0748
2007	39,533	37,015	2,518	.0637

Notes: A product code HS-1992 is considered "uniquely mapped" if according it is uniquely mapped according to our mapping HS-1992→HS-1996 → NACE built using the conversion tables from RAMON (HS 2007 to CPA) and Comtrade (HS1992 to HS2007). Each observation for product HS1992 that cannot be uniquely mapped to a NACE sector is dropped (either because there is no mapping or the mapping is not unique). Column (4) displays the the trade value non-uniquely matched products as the share of overall imports French imports from China. Trade values are expressed in current dollars.

B Formulating aggregate predictions on the basis "deviation from cross-sectional average" estimates

In this section, I analyze a univariate linear data generating process with a fixed-effect (intercept) common to the entire cross-section that is a function of the realized average of the regressor. The goal is to illustrate the difference between the set of assumptions required to obtain consistent estimate of individual effect and that required to make aggregate predictions.

Let us consider the following GDP:

$$y_i = \mu + x_i\beta + u_i \tag{7}$$

We assume $E(x_i u_i) = 0$, so that we sidestep issues associated with endogenous regressor. For simplicity and without loss of generality, we also assume that $E(x_i) = 0$. Realization of x_i and u_i are assumed to be i.i.d.

Now, we specify μ as being a function of the (un-weighted) sample mean $\overline{x}_N$.[30]

$$\mu := \mu(\overline{x}_N) = \delta + \overline{x}_N\alpha \tag{8}$$

So while δ and α are fixed parameters, μ is itself a random variable. Note also that $\overline{x}_N\alpha$ introduces a rough notion of spill-overs between units i's. Hence while x_i and u_i are i.i.d, y_i are not.[31].

In this context, making an "aggregate prediction" is to analyze of the conditional expectation of the cross-sectional average of y_ss conditional on that of x_is, i.e. $E(\overline{y}_N|\overline{x}_N)$. Under the stated assumption, we have:

$$\frac{\partial E(\overline{y}_N|\overline{x}_N)}{\partial \overline{x}_N} = \alpha + \beta \tag{9}$$

This expression contrasts with the individual effect of x_i on the conditional expected value of y_i.

$$\frac{\partial E(y_i|x_i)}{\partial x_i} = \alpha \times \frac{\partial E(\overline{x}_N|x_i)}{\partial x_i} + \beta = \frac{\alpha}{N} + \beta \tag{10}$$

Throughout the paper, we include period-fixed effect, which in the context of the DGP above, is akin to using an OLS estimator in deviation from the cross-sectional average.

$$\hat{\beta}_{OLS} = \frac{\sum_i^N (y_i - \overline{y}_N)(x_i - \overline{x}_N)}{\sum_i^N (x_i - \overline{x}_N)^2} \tag{11}$$

Substituting Equations 7 and 8, we obtain:

$$\hat{\beta}_{OLS} = \beta\frac{\sum_i^N (x_i - \overline{x}_N)(x_i - \overline{x}_N)}{\sum_i^N (x_i - \overline{x}_N)^2} + \frac{\sum_i^N (u_i - \overline{u}_N)(x_i - \overline{x}_N)}{\sum_i^N (x_i - \overline{x}_N)^2} = \beta + \frac{\sum_i^N (u_i - \overline{u}_N)(x_i - \overline{x}_N)}{\sum_i^N (x_i - \overline{x}_N)^2} \tag{12}$$

Clearly under the assumption $E(x_i u_i)$, we have plim $\hat{\beta}_{OLS} = \beta$.

[30]The use of a weighted mean does not change the nature of the argument.

[31]It is a special case of a spatial lagged in x model where the weighing matrix contains only $1/N$ as entries. It is straightforward to extend the argument to more general weighing matrix, allowing for instance $\overline{x}_N\alpha$ to be a weighted rather than a simple average, as long as the weights are not i-specific, therefore ensuring that aggregate effects can be properly "taken out" by demeaning.

It suggests that in the case where the common intercept is a function of the mean of the regressor, using cross-sectional variation in deviation from the aggregate trend only allows to obtain an approximation of $\frac{\partial E(y_i|x_i)}{\partial x_i}$.

However, as N grows to infinity,[32] we have: $\frac{\partial E(y_i|x_i)}{\partial x_i} \longrightarrow \beta = \text{plim } \hat{\beta}_{OLS}$. Hence assuming $\alpha = 0$ is not required to retrieve consistent estimates of $\frac{\partial E(y_i|x_i)}{\partial x_i}$.

However, $\frac{\partial E(\overline{y}_N|\overline{x}_N)}{\partial \overline{x}_N}$ does not become arbitrarily close to β as N grows large. Moreover, α cannot be identified using an estimator based on deviations from the cross-sectional average. As a result, when making aggregate predictions, it becomes necessary to make an assumption on the sign and magnitude of α. I assume $\alpha = 0$ throughout the paper, which appears to lead to conservative predictions as one would expect negative spill-overs across local labor markets (in this example $\frac{\partial E(y_i|x_i,x_j)}{\partial x_j} = \frac{\alpha}{N} < 0$), suggesting that $\alpha < 0$.

[32] I focus on asymptotic results because in the paper, estimation is carried out using instrumental variable estimator which has desirable properties asymptotically but not in finite samples. Moreover, given the large number of observations (348 by cross-section) it seems reasonable to consider the case where $\alpha/N \approx 0$.